CHAPTER 4
RESULTS AND DISCUSSION

4.1 CHAPTER INTRODUCTION

Figure 4.1 illustrates the flow of Chapter 4. The data sets used for the experiments are presented in Section 4.2. In Section 4.3, the results of neural fuzzy segmentation is presented and discussed. The fuzzy neural segmentation results are analyzed in Section 4.4. Chapter 4 is summarized in Section 4.5.

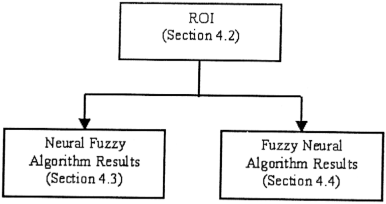


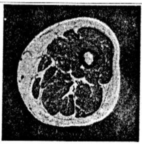
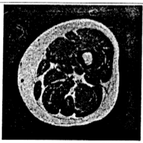
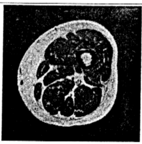
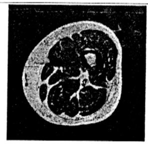
Figure 4.1 – Overview of Chapter 4

4.2 REGION OF INTEREST (ROI)

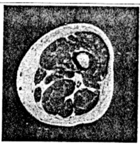
Table 4.1 shows the first MRI data set used in this project. The first MR image is taken at the femur shaft and the last slice is taken near the knee region. The original sizes of the images used are 256 x 256 pixels. Table 4.1 shows the original images of the first MR data set. The size of the ROI manually selected is 64 x 90 pixels. The ROI selected is shown in Column 2 of Table 4.2 and Table 4.3. The black ring in the images is the femur region. The bone marrow is the white region in the middle of the black ring. Bone is dark in color due to its low water content (see Section 2.3.5). Bone marrow is lightest in color because of its high water content. The gray region around the femur is the soft tissue.

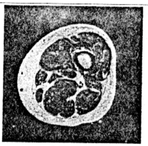
MR images of Data Set 2 (Table I), Data Set 3 (Table IV) and Data Set 4 (Table VII) are illustrated in Appendix A. The ROI of Data Set 2, Data Set 3 and Data Set 4 are illustrated in Column 2 of Table III, Table VI and Table IX respectively in Appendix A. The same ROI images are used for neural fuzzy segmentation and fuzzy neural segmentation.

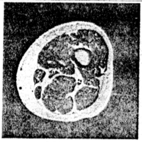
Table 4.1 – Original MR Images of Data Set 1

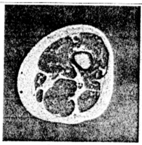
 **Slice 1**	 **Slice 2**	 **Slice 3**
 **Slice 4**	 **Slice 5**	 **Slice 6**

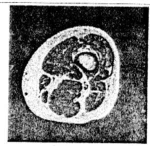

Slice 7

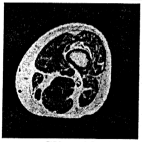

Slice 8

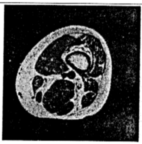

Slice 9

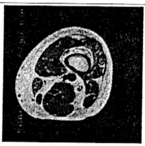

Slice 10


Slice 11


Slice 12

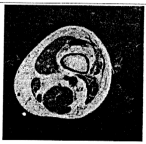

Slice 13

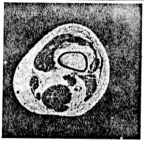
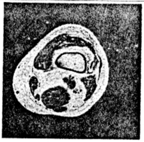

Slice 14


Slice 15


Slice 16


Slice 17


Slice 18

 **Slice 19**	 **Slice 20**	

4.3 NEURAL FUZZY ALGORITHM RESULTS

Sample results of each processing steps described in Section 3.4 are discussed in the following sub-sections.

4.3.1 SELF ORGANIZING MAPS (SOM) CLASSIFICATION

The first step in the segmentation process is SOM classification. For Data Set 1, a six-output class SOM network is used to classify the ROI images. Column 3 in Table 4.2 shows the results of the SOM classification, with the respective ROI images in Column 2. SOM network is able to map the input images more accurately if it has more output classes.

SOM classification parameters and results for the other data sets are shown in Appendix A. Column 3 of Table III, Table VI and Table IX illustrate the results of SOM classification for Data Set 2, Data Set 3 and Data Set 4 respectively.

4.3.2 FUZZY CLASSIFICATION

Fuzzy classification uses the output of SOM network. The output classes from SOM neural network is used to calculate the mean and variance of each output class. Then, the variables are used to calculate the Gaussian membership function for the output classes. Figure 4.2 shows the membership functions of Data Set 1.

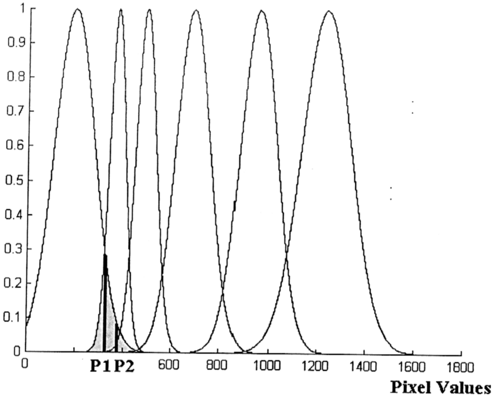


Figure 4.2 – Membership Functions of Data Set 1

During the defuzzification process, the first 2 membership functions with the lowest mean are used. The fuzzy minimum operation is performance on the membership functions. In this data set, it is found that max-membership principle defuzzification method gives the optimal defuzzification value, P2, for Slice 1 to Slice 12. For Slice

13 to Slice 20, the centroid defuzzification method gives the optimal defuzzification value, P1. Figure 4.2 illustrated the results of the minimum function (gray region) and the optimal defuzzification values, P1 and P2. For Slice 1 to Slice 12, pixel values smaller than P2 are labeled as bone region. All other pixel values are labeled as non-bone region. The process is repeated for Slice 13 to Slice 20. For these slices, pixel values smaller than P1 are labeled bone region and pixel values higher than P1 are labeled as non-bone region. The output fuzzy classification is binary images shown in Column 4 of Table 4.2.

The details of fuzzy classification for the other data sets are given in Appendix A along with the classification results. Column 4 in Table III, Table VI and Table IX show the results of fuzzy classification for Data Set 2, Data Set 3 and Data Set 4 respectively.

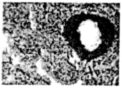
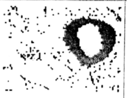
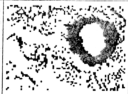
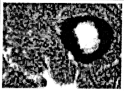
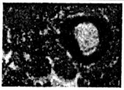
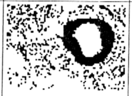
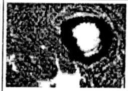
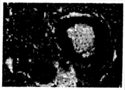
4.3.3 ARTIFACT REMOVAL

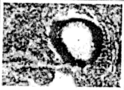
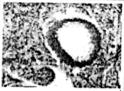
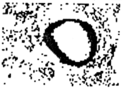
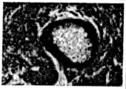
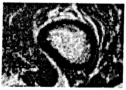
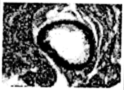
The artifact removal technique explained in Section 3.6 is applied to the images from the fuzzy classification. A 4-neighborhood connectivity is used to select the bone region and to remove artifacts. The results are displayed in Column 5 Table 4.2. It is noticed that this process is not able to remove all the artifacts present in the final images. Manual intervention may be required to obtain finer results, but it is not used in this thesis.

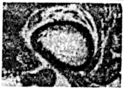
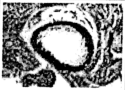
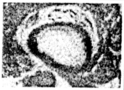
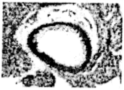
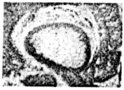
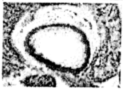
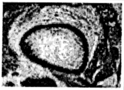
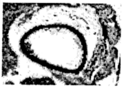
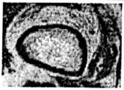
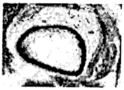
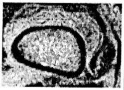
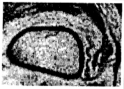
The final results for the other data sets are in Appendix A. Column 5 of Table III,

Table VI, and Table IX displays the final segmentation results of Data Set 2, Data Set 3 and Data Set 4 respectively.

Table 4.2 – Neural Fuzzy Segmentation Results of Data Set 1

Slice	ROI	SOM	Fuzzy	After Artifacts Removal
1				
2				
3				
4				
5				
6				

Slice	ROI	SOM	Fuzzy	After Artifacts Removal
7				
8				
9				
10				
11				
12				
13				

Slice	ROI	SOM	Fuzzy	After Artifacts Removal
14				
15				
16				
17				
18				
19				
20				

4.3.4 3D MODEL CONSTRUCTION

The binary images in Column 5 of Table 4.2 are used to construct a 3D model of the femur. Figure 4.3 shows the rendered volume model of the femur.

Figure 4.3 – 3D Model of Femur Segmented from Data Set 1

4.2.5 DISCUSSION OF NEURAL FUZZY SEGMENTATION

There are a number of parameters to monitor to ensure good segmentation results. The parameters are :

- the training epoch of SOM network
- the number of output SOM network classes.
- the membership functions used for defuzzification
- the fuzzy operator used for defuzzification (minimum or maximum)
- the defuzzification method used (Section 2.7.5)

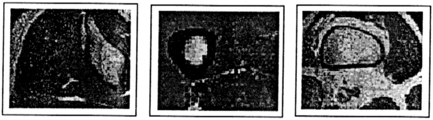
The parameters above have to be adjusted during experiment to obtain the optimum values, and to acquire good segmentation results.

The neural fuzzy algorithm produces partially extracted femur at the knee region, where the segmented femur is broken at certain regions (Slice 20, Table 4.2). The algorithm is also unable to remove artifacts sufficiently, when the final segmented bone is not smooth (Slice 12, Table 4.2). If different defuzzification method (other than max membership principle method) are used for Slice 1 to Slice 12, there is a lot of bone lost or too much artifacts in the final segmented images. This also applies to Slice 13 to Slice 20.

Table 4.2 give the results of all segmented MR images. When the images are compared with the original image, the accuracy of segmentation requires improvement. For example, the segmented bone in Slice 20 is incomplete, where the bone ring is broken.

Manual segmentation of the femur is not feasible due to the large amount of data. Automated segmentation methods that performs well and robust enough for clinical studies are also not applicable to MRI data [2]. The algorithm given in this thesis avoids both extremes and proposes a semi-automated approach for segmentation of MR images of the femur. The algorithm requires the adjustment of many parameters interactively to yield good segmentation results.

The segmentation algorithm is able to extract the femur from transverse MR images with low computational resources and processing time. However, it is time consuming when many parameters in the fuzzy classification step need to be fine tuned to obtain good segmentation results. In this step, the parameters to process different region of the femur need to optimized for better segmentation. For example, in Data Set 1, two defuzzification methods need to be applied to the data set, max-membership principle method for the first half of the slices (Slice 1 to Slice 12) and centroid method for the other half (Slice 13 to Slice 20). This is because the femur bone is not symmetrical and the thickness of the bone along the femur is not consistent. The femur bone at both ends (hip and knee) (Figure 4.4(a) and Figure 4.4(c)) is thinner than those at the femur shaft (Figure 4.4(b)). This requires extra consideration to obtain better segmentation of the femur. Larger data sets may require more time to fine tune the fuzzy classification parameters for good segmentation of the femur.



(a) (b) (c)

Figure 4.4 – MR Scan of the Human Femur (a)Thin Femur Bone at the Hip Region (b)Thick Bone at Femur Shaft (c)Thin Femur Bone at the Knee Region

It is not possible to directly validate the segmentation results because the scans were taken from actual life samples. The segmentation correction can be determined using apriori knowledge of the anatomical structure of a healthy human femur. The segmentation results are also compared with the ROI images to validate segmentation results.

4.4 FUZZY NEURAL ALGORITHM RESULTS

Sample results of each processing step described in Section 3.5 are discussed in the following sub-sections. The MR image data sets used in the experiment and the corresponding results are discussed.

4.4.1 OBTAINING FUZZY MEMBERSHIP FUNCTIONS

The first image in Data Set 1 (Slice 1, Table 4.1) is used to obtain the membership functions of the different tissues. In the image, there are three different tissues that can be distinguished :- bone, soft tissue and bone marrow (Figure 3.7). Sample data points from the different tissues in the image are selected manually. The more sample points selected from the image, the more accurate the membership functions. Usually, 20 sample points for each tissue is sufficient.

Once the data points are available, the membership functions are calculated using the entropy minimization principle described in Section 3.5.1. The first three membership functions obtained after secondary partitioning is illustrated in Figure 4.5.

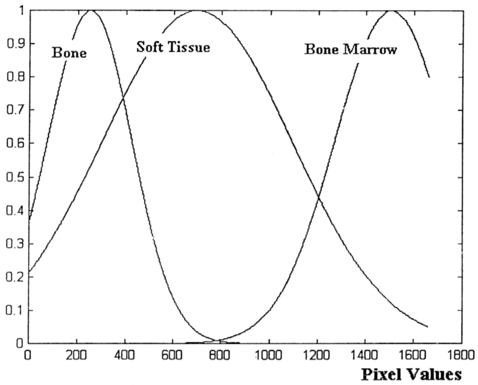


Figure 4.5 – Three Membership Functions of a MR Image

The membership functions in Figure 4.5 are further partitioned into six different membership function by applying the entropy minimization principle again. Figure 4.6 illustrates the six different membership functions of the MR image.

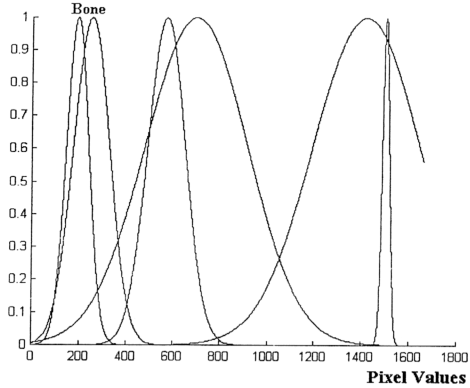


Figure 4.6 – Six Membership Functions of a MR Image

After the membership functions are obtained, overlap areas between the membership functions are defuzzified. For Data Set 1, the centroid defuzzification method is used as it produces the best classification results. The defuzzification values are used to reduce the gray level values of the MR image to six gray level values. The results of fuzzy classification are images with six gray level values, illustrated in Column 3 of Table 4.3 in comparison with the ROI in Column 2. The images from fuzzy classification are then used as input for SOM neural network.

The fuzzy classification results for Data Set 2, Data Set 3 and Data Set 4 are illustrated in Appendix B in Column 3 of Table X, Table X1 and Table XII respectively

4.4.2 SELF ORGANIZING MAPS (SOM) CLASSIFICATION

The next step in the segmentation process is the SOM classification. For Data Set 1, the six classes from fuzzy classification is used as input for the SOM neural network. The SOM network is able to map the input image more accurately if it has more output classes. The SOM network is set to output six different classes. The bone class can be selected visually from the SOM neural network results. Column 4 in Table 4.3 shows the results of SOM classification, with the respective ROI images in Column 2. SOM network is not able to segment the image as it produces good results with many output classes. The output image with the femur bone had a iot of artifacts. Thus the images are processed further to remove the artifacts.

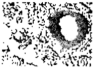
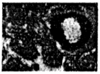
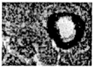
SOM classification results of the other data sets are in Appendix B. Column 4 of Table X, Table XI and Table XII illustrate the results of SOM classification for Data Set 2, Data Set 3 and Data Set 4 respectively.

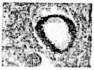
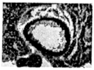
4.4.3 ARTIFACT REMOVAL

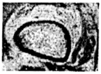
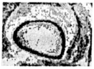
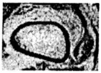
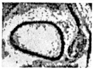
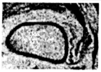
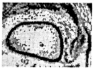
The artifact removal technique explained in Section 3.6 is applied to the images from the SOM classification. A 4-neighborhood connectivity is used to select the bone region and remove artifacts. The results are displayed in Column 5 of Table 4.3. It is noticed that this process is not able to remove all the artifacts present in the final images. Manual intervention may be required to obtain finer results for slices 1 to 16. For Slices 17 to 20 it is noticed that the segmentation is good, with minimal artifacts and no broken femur ring. Manual removal of artifacts is not used in this thesis.

The final results for the other data set are in Appendix B. The artifacts from the other data sets could not be removed. Column 4 of Table X, Table XI, and Table XII displays the final segmentation results of Data Set 2, Data Set 3 and Data Set 4 respectively.

Table 4.3 – Fuzzy Neural Segmentation Results of Data Set 1

Slice	ROI	Fuzzy	SOM	After Artifacts Removal
1				
2				
3				
4				
5				
6				

Slice	ROI	Fuzzy	SOM	After Artifacts Removal
7				
8				
9				
10				
11				
12				
13				
14				

Slice	ROI	Fuzzy	SOM	After Artifacts Removal
15				
16				
17				
18				
19				
20				

4.4.4 3D MODEL CONSTRUCTION

The binary images obtained after artifacts removal could not be used to construct the 3D model of the femur. This is due to the high content of artifacts in the images.

4.4.5 DISCUSSION OF FUZZY NEURAL SEGMENTATION

The success of fuzzy neural segmentation depends on the membership functions obtained from the MR image. If more sample points are obtained for the different tissues, the membership functions that were calculated would be more accurate.

The different tissues in the MR image has to be visually apparent to ensure that more the membership functions can be calculated and defined. From the sample points in Data Set 1, six membership function were calculated as illustrated in Figure 4.6. After tertiary partitioning, 7 membership functions can be obtained (as explained in Section 3.5.1). However, from the data sample points, only six memberships can be calculated, as the "soft tissue" memberships function cannot be partitioned further.

SOM neural network is not able to segment the images from fuzzy classification as seen from Column 5 of Table 4.3. This is because SOM network map the input image more accurately if it has more output classes. The segmentation results for Slice 17 to Slice 20 are encouraging. This is because the contrast between the tissues are quite clear.

The fuzzy neural algorithm is also unable to remove artifacts sufficiently, whereby the final segmented bone is not smooth (Slice 1, Table 4.3). Manual intervention may be required to remove the artifacts.

4.5 CHAPTER SUMMARY

Chapter 4 presents the results of the MR segmentation using two algorithms namely, neural fuzzy algorithm and fuzzy neural algorithm. The neural fuzzy algorithm is able to segment the MR images to construct a 3D model of the femur. However, the fuzzy neural algorithm is only able to segment a portion of the MR images from the data set. Some of the images segmented using fuzzy neural algorithm contain a lot of artifacts (Slice 1 to Slice 12 in Table 4.3). The bone in the in other images (Slice 13 to Slice 20 in Table 4.3) are segmented well. The resulting images from the fuzzy neural algorithm cannot be used to construct the 3D model of the femur due to the high content of artifacts.